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Optimization of Bond Portfolio Using Risk Parity Analysis: Case Study on USD-Denominated Bonds Portfolio

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ABSTRACT

Portfolio optimization has become increasingly critical in an era marked by heightened financial market volatility, with global events such as the 2008 financial crisis and the COVID-19 pandemic exposing significant limitations in traditional asset allocation methodologies. This study examines the performance of the risk parity approach in optimizing USD-denominated fixed income portfolios, particularly for institutional investors such as central banks. The research addresses limitations in the traditional Mean-Variance Optimization (MVO) method, which is highly sensitive to input data and prone to concentration risk. Risk parity, also known as Equally Weighted Risk Contribution (ERC), distributes risk evenly across assets without relying on expected return estimates, thereby enhancing portfolio diversification. Using empirical data from 2014 to 2023, the study calculates risk contributions, constructs a covariance matrix, optimizes portfolio weights, and evaluates performance through the Sharpe ratio. The empirical findings reveal that although the MVO model achieved a slightly higher overall Sharpe ratio, the Risk Parity approach demonstrated superior stability and resilience across different market conditions, particularly during periods of high volatility such as the COVID-19 pandemic and post-pandemic financial tightening. These results suggest that Risk Parity, by emphasizing risk diversification over return forecasting, enhances portfolio robustness, making it an attractive strategy for conservative institutional investors focused on stability and capital preservation. The study highlights that portfolio optimization performance is context-dependent, with Risk Parity offering better protection in turbulent conditions, thereby supporting its broader adoption for risk-averse institutions in an increasingly uncertain global financial environment.

KEYWORDS *Risk Parity, MVO, Bonds, Portfolio Optimization, USD, Kupiec VaR test*

INTRODUCTION

The 2008 global financial crisis and the Covid-19 pandemic have had a profound impact on financial market participants, primarily by creating heightened uncertainty in obtaining investment returns. The classic method, mean-variance optimization (MVO), faced significant criticism—particularly during the 2008–

2009 global financial crisis—due to the poor performance of asset managers. In response, enhancing risk management tools became a top priority for investors. Today, risk-taking plays a central role in asset management, as it allows managers to strive for above-benchmark performance (Cassar & Grima, 2016).

The MVO method is considered to have several weaknesses, primarily its high sensitivity to input data in achieving an optimal asset allocation with the desired return (Ararat et al., 2024; Choi et al., 2024; Kolm et al., 2014; Maillard et al., 2010; Palit & Prybutok, 2024). These inputs mainly include outlook factors such as expected returns and risks based on projections of exchange rates, currencies, and spreads. Additionally, another drawback of MVO is its uneven asset allocation, which often leads to concentration in specific asset classes (Chaves et al., 2011; Maillard et al., 2010). These limitations highlight the need to explore alternative asset allocation optimization methods.

The risk parity portfolio, also known as the Equally Weighted Risk Contribution (ERC) portfolio, enables the creation of diversified portfolios in which resources are distributed according to risk measures so that each asset's risk contribution is the same (Ararat et al., 2024; Choi et al., 2024; Costa & Kwon, 2019; Kolm et al., 2014). These approaches eliminate the need to estimate expected returns, thereby significantly reducing estimation errors and naturally leading to well-diversified portfolios. However, while this minimizes one source of uncertainty, the risk parity approach still relies on estimating a risk measure, making it vulnerable to potential estimation errors and their adverse effects (Costa & Kwon, 2019).

This study specifically focuses on institutional investors, particularly central banks. Central banks typically adopt a conservative and cautious approach to portfolio management for foreign exchange reserves, aiming to minimize risk and ensure stability (Uz Akdogan, 2020). This approach supports effective monetary policy and long-term economic stability. A survey conducted by the Bank for International Settlements (7th BIS Reserve Management Practices Survey, 2024) across 120 central banks revealed that over 90% continue to focus their portfolio diversification on bonds, while exposure to riskier assets remains low—i.e., equities, commodities, and real estate. Bond selection varies widely, including U.S. government bonds, supranational bonds, corporate bonds, green bonds, and mortgage-backed securities (MBS).

Given this, research on asset allocation across various types of bonds for institutional investors, such as central banks, is both relevant and crucial to achieving optimal asset combinations. The survey also found that most central banks continue to invest heavily in U.S. dollars (USD) for their foreign exchange reserves, as the USD remains a stable and safe currency, particularly during economic turbulence. With the U.S.'s high credit rating, extensive international trade, and the world's most liquid financial markets, USD-denominated bonds continue to dominate the global bond market despite diversification efforts into other currencies. Therefore, this study focuses on USD-denominated bonds as the primary research subject.

USD-denominated bonds exhibit distinct characteristics that significantly influence portfolio management dynamics and risk profiles. First, USD bonds have lower default risk compared to local-currency bonds in emerging markets, as they are backed by the full faith and credit of highly rated sovereigns or corporations operating within the world's largest economy (Burger et al., 2018; Du & Schreger, 2016). Second, these bonds demonstrate unique liquidity characteristics—the USD bond market represents the deepest and most liquid fixed-income market globally—facilitating easier portfolio rebalancing and price discovery (Adrian et al., 2013; Fleming, 2003). Third, USD bonds face specific interest rate risk dynamics tied to Federal Reserve monetary policy, where policy rate changes have asymmetric and often amplified effects on bond prices compared to bonds denominated in other currencies (Bernanke & Kuttner, 2005; Gilchrist et al., 2015). Fourth, these instruments carry inherent currency risk for non-U.S. investors, introducing an additional layer of volatility that must be managed within the portfolio optimization framework (Maggiori et al., 2020; Jiang et al., 2021). Fifth, USD bonds exhibit distinct correlation structures with global equity markets and commodities—particularly during crisis periods—when the U.S. dollar tends to appreciate as a safe-haven currency, providing natural hedging properties (Ranaldo & Söderlind, 2010; Habib & Stracca, 2012).

Finally, the diverse types of USD bonds—ranging from U.S. Treasuries to supranational bonds, corporate bonds, mortgage-backed securities, and emerging market bonds—each carry different credit risk profiles, liquidity premiums, and sensitivities to macroeconomic factors. This creates a complex optimization landscape in which risk parity approaches may offer particular advantages in balancing heterogeneous risk exposures (Longstaff et al., 2011; Schwarz, 2019). These characteristics make USD bonds an ideal testing ground for comparing risk parity and mean-variance optimization approaches, as the effectiveness of each may vary depending on how well they accommodate these unique market features.

The empirical strategy of this research involves five key steps to analyze the performance of USD-denominated bond portfolios using the risk parity approach. First, daily return data for each bond index from 2014 to 2023 is calculated, and standard deviations or variances are computed as proxies for investment risk. Second, the risk contribution (RC) of each asset to total portfolio risk is determined, followed by the calculation of the relative risk contribution (RRC), representing the ratio of RC to total portfolio risk. After obtaining RRC values for each bond type, a covariance matrix is constructed for a portfolio comprising five distinct bond types. In the third stage, the return and risk data are processed to determine optimal portfolio weights using the risk parity method. Lastly, the Sharpe ratio is computed to evaluate the performance of the risk parity approach in optimizing portfolio returns relative to risk.

The same calculation process is applied to the MVO method for comparison. This research evaluates the effectiveness of the risk parity method through a comparative analysis of Sharpe ratios, ensuring a robust assessment of its performance relative to the alternative method. Findings indicate that risk parity provides balanced risk contributions, allowing for greater diversification and reducing concentration risk (Chaves et al., 2011). Due to superior risk diversification, risk parity portfolios often exhibit lower drawdowns during periods of market turbulence or high volatility. Although risk parity may not always generate the highest absolute returns, it tends to deliver more consistent and stable long-term performance (Cesarone et al., 2020).

This study aims to evaluate asset allocation performance in a USD-denominated fixed-income portfolio using the risk parity approach. The research has two primary motivations. First, prior studies have examined portfolio optimization using the risk parity approach across various asset classes, such as Cesarone et al. (2020) and Cho & Song (2023), who explored portfolio construction involving international equity indices like the Dow Jones Index, S&P 500, and Euro Stoxx 50. Additionally, Choi et al. (2024) explored risk parity in stock and ETF assets, while Ararat et al. (2024) investigated risk parity across ETFs, bonds, and commodities. Despite these efforts, the study of risk parity optimization for bond assets remains limited. This study fills that gap by providing new perspectives and empirical evidence on risk parity optimization in USD-denominated bonds. Second, it compares the performance of the risk parity approach with the traditional MVO method.

The main contributions of this study are as follows. First, it extends the existing literature on the risk parity method. Compared to prior empirical research that focused on broader asset classes with minimal attention to bonds, this study analyzes the implementation of risk parity across diverse bond types with distinct risk characteristics. Second, the study offers an alternative framework for institutional investors to devise appropriate asset allocation strategies by aligning desired risk–return profiles with improved performance outcomes.

RESEARCH METHOD

This study utilized quantitative comparative analysis methods and adopted an empirical research design to investigate the construction of an optimal bond portfolio weight. The study encompassed secondary data sources, utilized the daily closing prices of the index bonds to compute their daily returns. This study analyzed

2.501 daily data points for each the index bonds. This study obtained 5 (five) daily index return data from the past ten years, covering the period from 2014 to 2023, consists of USD-denominated bond portfolios, including the government bond index, supranational bond index, corporate bond index, and mortgage bond index, sourced from the index provider Bloomberg. To analyze the data, a solver technique in Microsoft Excel was used.

Table 1. Description of the Bond Index

No	Bond Index Category	Index Name	Bloomberg Ticker	Description
1	US Government Bonds	Bloomberg US Treasury Total Return Index	LUATTRUU Index	Represents US Treasury securities across all maturities, serving as the risk-free benchmark for USD-denominated fixed income
2	Supranational Bonds	Bloomberg Supranational USD Total Return Index	BSUPUSD Index	Comprises bonds issued by multilateral development banks and international organizations with high credit quality
3	US Mortgage-Backed Securities (MBS)	Bloomberg US MBS Total Return Index	LBUSTRUU Index	Tracks agency mortgage-backed securities issued or guaranteed by US government-sponsored enterprises
4	US Corporate Bonds	Bloomberg US Corporate Total Return Index	LUACTRUU Index	Covers investment-grade corporate bonds issued by US companies across various sectors
5	Emerging Market Bonds	Bloomberg EM USD Aggregate Total Return Index	EMUSTRUU Index	Represents USD-denominated sovereign and corporate bonds from emerging market economies

Source: Bloomberg Terminal, Authors' Compilation

A considerable many of literature has examined various methodologies aimed at enhancing portfolio performance while concurrently mitigating risk exposure. Among the widely studied approaches are Mean-Variance Optimization (MVO), Conditional Value-at-Risk (CVaR) optimization, the Single Index Model (SIM), the Capital Asset Pricing Model (CAPM), Risk Parity, and the Black-Litterman model. The appropriateness of each technique is largely influenced by investor preferences, prevailing market conditions, and the specific objectives of the investment strategy. Consequently, investors often adopt a flexible approach, combining or adapting these models to better align with their unique requirements and market expectations.

The present study aims to investigate the comparative effectiveness of modern models, such as Risk Parity, which focus on risk allocation, and traditional models, such as MVO, which emphasize return maximization. Both of which method have not been thoroughly studied focusing in USD denominated bond market. Risk Parity strategies prioritize the allocation of risk rather than the maximization of returns, aiming to achieve a more balanced and diversified risk profile across portfolio assets. MVO constructs the efficient frontier to identify optimal portfolios that minimize risk for a given level of expected return or maximize return for a given level of risk, utilizing the covariance matrix to evaluate the interrelationships among assets.

Variables measurement

The bond index return was measured using the following formula:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$$

where, $R_{i,t}$ is the return of bond index i; $P_{i,t}$ is the closing price of the bond index i at time t; $P_{i,t-1}$ is the closing price of the bond index i at time t-1.

After calculating the return of the bond index, the variance for each bond index is estimated Eq. below:

$$\sigma_i^2 = \frac{\sum_i^n (R_i - E(R)_i)}{n-1}$$

To fulfill the requirements for selecting the optimal Markowitz portfolio, the expected return of the portfolio is calculated. To do so, the optimal weights of the assets that make up the portfolio must be extracted using the matrix multiplication as follows:

$$E(R_p) = w^T R = [w_1, \dots, w_i] \begin{bmatrix} E(R_1) \\ . \\ . \\ . \\ E(R_i) \end{bmatrix}$$

where, w is the weight vector of the bond index (1, …, j) in the portfolio, and R is the expected return vector of the bond index (1, …, i) in the portfolio.

Following the calculation of the portfolio's return, the total risk (variance) can be determined using the following Eq:

$$\sigma_p = \sqrt{w^T S(w)} = \left[[w_1 \dots w_i] \begin{bmatrix} \sigma_{11} \dots \sigma_{1i} \\ . \\ . \\ . \\ \sigma_{i1} \dots \sigma_{ii} \end{bmatrix} \begin{bmatrix} w_1 \\ . \\ . \\ . \\ w_i \end{bmatrix} \right]^{\frac{1}{2}}$$

The portfolio standard deviation is as Eq

where, S represents the variance-covariance matrix of the covariance between each of the bond index returns in the portfolio. Variance-covariance between the returns of any two different bond index, calculated according to the following formula:

$$S = \sigma_{x,y} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x}\ )(y_i - \bar{y})$$

Risk-parity optimization model

The principle of risk parity portfolios is to determine resource allocation by distributing wealth in such a way that each asset has an equal contribution to the overall portfolio risk (Costa & Kwon, 2019; Maillard et al., 2010). The risk parity approach suggests that equalizing the risk contribution across assets can enhance the portfolio's Sharpe ratio and strengthen its resilience during market downturns (Ararat et al., 2024; Cesarone et al., 2020). Fundamentally, the concept mirrors the classic '1/n' portfolio, where wealth is distributed equally among all assets. For this reason, risk parity portfolios are sometimes referred to as ERC portfolios.

The distribution of wealth by equal risk contribution is entirely dependent on the measure of risk selected. For a portfolio with n assets, the variance or portfolio volatility are given by:

$$\sigma(w) = \sqrt{w^T \sum w}$$

where $\sigma(w)$ is the calculation of portfolio variance, Σ is the covariance matrix, w is the investment allocation and w^T is the transpose of the same allocation matrix. Then RC is calculated based on the risk contribution of asset i to the total portfolio risk.

$$RC_i = \frac{w_i\,(\sum w)_i}{\sqrt{w^T \sum w}}$$

From this calculation, the total Risk Contribution (RC) of each asset class will be equal to the total portfolio risk.

$$\sum_{i=1}^{N} RC_i = \sigma(w)$$

Furthermore, the relative risk contribution (RRC) is calculated based on the ratio of RC to the total portfolio risk.

$$RRC_i = \frac{RC_i}{\sigma(w)} = \frac{w_i\,(\sum w)_i}{w^T \sum w}$$

The RRC calculation is carried out with the aim of $\sum_{i=1}^{N} RRC_i = 1$ atau allocation of investment weights so that all assets have the same risk contribution. The portfolio risk parity method will equalize the risk contribution.

$$RC_i = \sigma(w)/N$$

$$RRC_i = 1/N$$

In the Risk Parity approach, portfolio weights are determined such that each asset contributes equally to the total portfolio risk. Unlike MVO, Risk Parity does not rely on expected return forecasts, focusing instead on balancing risk across assets based on the covariance structure. The purpose is to attempt to achieve equal risk contributions, so, this can be obtained by minimizing the differences between the terms w_i and $\sum w_i$. So, w. So, w can be minimized by:

$$\sum_{i,j=1}^{N} (w_i(\Sigma w)_i - w_i(\Sigma w)_i)^2 - F(w)$$

Mean-Variance Optimization (MVO) model

The MVO model proposed by Harry Markowitz is utilized to construct the optimal investment portfolio. The objective is to maximize the Sharpe ratio, which measures the excess return per unit of risk. Excel Solver is employed as the optimization tool to determine the optimal weight allocation for each asset in the portfolio. The optimization model is designed as follows:

$$Max \sum_{i=1}^{N} \frac{w_i R_i - R_f}{\sigma_i}$$

where w_i represents the weight of asset i, Ri is the expected return of asset i, Rf is the risk-free rate, and σi denotes the standard deviation of asset i. By maximizing this function, the portfolio aims to achieve the highest possible Sharpe ratio, thus offering the most efficient trade-off between risk and return.

For the traditional Markowitz Mean-Variance Optimization, the expected portfolio return E (Rp) is calculated as:

$$E(R_p) = w^T R$$

where:

w = weight vector of the bond indices in the portfolio,

R = expected return vector for each bond index.

The goal of MVO is to find the weight vector that either minimizes portfolio risk for a given level of expected return or maximizes expected return for a given level of risk. The implementation of this model involves several steps: calculating the expected returns, standard deviations, and covariances of the assets based on historical data, setting up the optimization problem in Excel Solver, and applying constraints such as the sum of asset weights equaling one and, if needed, restrictions on individual asset weights. Through this process, the efficient frontier can be derived, and investors can select portfolios that align with their specific risk-return preferences. This methodology provides a structured, quantitative approach to portfolio selection, rooted in modern portfolio theory.

Optimal Portfolio Criteria

One approach to determining the optimal portfolio composition is based on the Sharpe ratio criteria, also referred to as the reward-to-risk ratio. According to Sharpe (1994), the Sharpe ratio reflects the additional return an investor receives for taking on a certain level of risk. The formula for the Sharpe ratio, as presented by (Bodie et al., 2024), is as follows:

$$S = \frac{\left[E(R_p) - R_f\right]}{\sigma(R_p)}$$

where, S is the Sharpe ratio portfolio, and Rf is risk free return, and σ (R_p) is standard deviation of the expected return portfolio.

Backtesting with Value at Risk (VaR)

Kupiec (1995) introduced the concept of Value at Risk (VaR), a financial risk measurement method that estimates the maximum potential loss of a portfolio over a specific time period at a given confidence level. For example, a daily VaR of USD 1 million at a 99% confidence level indicates a 1% probability that the daily loss will exceed USD 1 million. VaR has undergone significant development and has been widely adopted in international banking regulations, including the Basel Accord, which uses the 99% VaR as a primary benchmark for market risk management.

Despite providing a concise and standardized measure of risk, VaR has notable limitations. It fails to account for extreme loss scenarios (tail risk) and does not provide information on the magnitude of losses exceeding the VaR threshold. Therefore, model validation through backtesting becomes crucial. Backtesting is the process of comparing estimated VaR with actual realized losses, enabling institutions to evaluate the accuracy and effectiveness of their VaR models. The primary goal of backtesting is to determine whether the VaR model consistently provides reliable risk estimates. Kupiec (1995) proposed the Proportion of Failure (POF) Test, a statistical approach to verify the accuracy of VaR predictions. The POF Test evaluates the null hypothesis:

$$H_0: p = \pi$$

where:
p is the empirical frequency of exceptions,

π is the expected exception rate based on the VaR confidence level.

Statistically, the Kupiec POF Test uses a likelihood ratio test to assess whether the observed frequency of exceptions matches the expected rate implied by the confidence interval. If the test statistic exceeds the critical value of the chi-square (χ^2) distribution, the model is deemed inaccurate. The likelihood ratio statistic is calculated as:

$$LR_{POF} = -2 \ ln \left(\frac{(1-p)^{T-x}.p^x}{(1-\pi)^{T-x}.\pi^x} \right)$$

where:
x = number of exceptions,
T = total number of observations,
p = observed exception frequency,
π = 1 – confidence level (i.e., the expected exception rate).

The test statistic LRPOF follows a chi-square distribution with one degree of freedom. If the calculated statistic exceeds the critical value of the $\chi^2(1)$ distribution, the null hypothesis is rejected, indicating that the VaR model is unreliable.

RESULTS AND DISCUSSION

Descriptive Statistics

The analysis of daily return movements for USD-denominated bond asset classes over the 2014–2023 period (Figure 1) reveals distinct phases of stability and volatility, closely aligned with global economic events. The USD-denominated bond market is generally characterized by fluctuating movements, primarily influenced by various global events that affect central bank interest rate policies, particularly in the United States. Several key events have shaped these dynamics, including the global economic slowdown and the Federal Reserve's shift from the end of quantitative easing (QE), which led to interest rate hikes in 2015, followed by further rate increases and the US-China trade war in 2018. Subsequent factors include the economic slowdown in 2019, the onset of the COVID-19 pandemic and the substantial monetary stimulus through interest rate cuts starting in 2020, and the post-pandemic recovery phase observed in 2022.

From 2014 until late 2019, the returns across U.S. Government Bonds, Supranational Bonds, MBS Bonds, Corporate Bonds, and Emerging Market Bonds generally exhibited low to moderate volatility, reflecting a period of relative financial stability and supportive monetary policies. However, beginning in early 2020, significant spikes in volatility are evident across all bond classes, coinciding with the outbreak of the COVID-19 pandemic. Emerging Market Bonds and Corporate Bonds, in particular, experienced sharper negative returns, highlighting their higher sensitivity to global risk sentiment compared to the more stable U.S. Government and Supranational Bonds. Although markets partially stabilized in late 2020 and throughout 2021, the return volatility remained elevated relative to pre-pandemic levels.

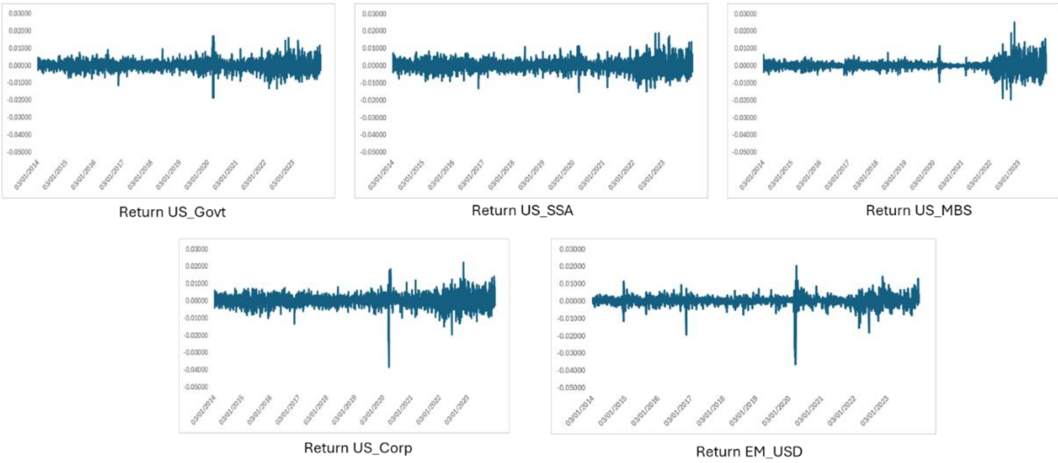


Figure 1. Daily Return History by Asset Class

The data further indicate a renewed period of heightened volatility during 2022–2023, driven by aggressive monetary tightening as central banks responded to rising inflation. During this phase, Corporate and Emerging Market Bonds again showed pronounced swings, while MBS Bonds exhibited greater sensitivity to interest rate shocks. Meanwhile, U.S. Government Bonds remained the most resilient asset class, with comparatively stable return patterns even during episodes of market stress, reinforcing their traditional role as safe-haven assets. The events of 2023, particularly the collapse of Silicon Valley Bank and banking sector instability, further contributed to sharp movements in bond returns. Overall, the observed patterns confirm that riskier bond assets exhibit amplified volatility during periods of systemic stress, whereas MBS bonds, high-grade government and supranational bonds provide greater portfolio stability under adverse economic conditions.

Table 2. The descriptive statistics of the samples' daily returns

	US Govt Bonds	**US Supranational Bonds**	**US MBS Bonds**	**US Corporate Bonds**	**EMUSD Bonds**
Mean Return (Annual)	1.375%	1.936%	1.486%	3.083%	3.109%
StdDev (Daily)	0.304%	0.339%	0.272%	0.368%	0.288%
StdDev (Annual)	4.829%	5.381%	4.323%	5.839%	4.564%
Median	0.010%	0.009%	0.013%	0.025%	0.022%
Sharpe Ratio	0.285	0.360	0.344	0.528	0.681

Source: Authors elaboration using data from Bloomberg 2014–2023.

Table 2 presents descriptive statistics for five USD-denominated bond indices: U.S. Government Bonds, Supranational Bonds, MBS Bonds, Corporate Bonds, and Emerging Market (EM) Bonds. Results indicate that Corporate Bonds and EM Bonds deliver the highest annualized mean returns, at 3.083% and 3.109% respectively, while Government Bonds exhibit the lowest return at 1.375%. In terms of risk, measured by annualized standard deviation, Corporate Bonds show the highest volatility (5.839%), whereas MBS Bonds present the lowest (4.323%). The median returns across all bond classes are positive, indicating a general tendency for gains over the sample period. These descriptive statistics highlight that although EM and Corporate Bonds offer higher return opportunities, they also expose investors to greater volatility compared to safer assets like Government and Supranational Bonds. Overall, the distribution of returns suggests a risk-return tradeoff consistent with traditional financial theory, with Emerging Markets and Corporate debt presenting higher risk premiums.

Meanwhile, if the returns are evaluated annually, the following results are obtained on Table 3 and Figure 2:

Table 3. The Annualized Return by Asset Class

Year	US Govt Bonds	US Supranational Bonds	US MBS Bonds	US Corporate Bonds	EMUSD Bonds
2014	4.921%	7.201%	6.066%	7.137%	4.747%
2015	0.933%	1.808%	1.536%	-0.547%	1.333%
2016	1.117%	0.926%	1.693%	6.072%	9.585%
2017	2.349%	2.812%	2.490%	6.329%	7.938%
2018	0.910%	1.226%	1.030%	-2.514%	-2.478%
2019	6.775%	8.116%	6.226%	13.774%	12.451%
2020	7.922%	8.327%	3.847%	9.828%	6.688%
2021	-2.276%	-2.287%	-1.036%	-0.923%	-1.634%
2022	-13.204%	-13.846%	-12.357%	-16.941%	-16.517%
2023	4.245%	5.024%	5.324%	8.534%	8.897%

Source: Authors elaboration

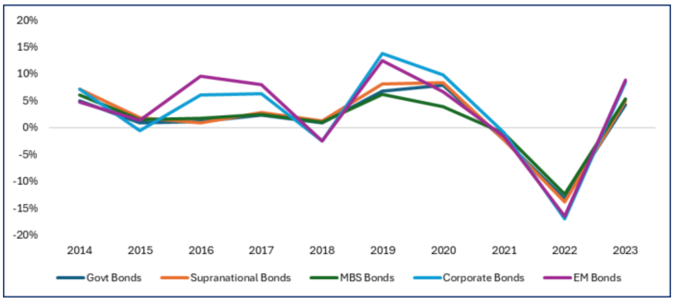


Figure 2. The Annualized Return by Asset Class
Source: Authors elaboration

In terms of asset classes, US Government bonds and US Supranational bonds typically provide relatively lower and stable returns, accompanied by minimal risk, owing to the strong credit support from the US government or other sovereign entities. Conversely, US Mortgage-Backed Securities (MBS) offer slightly higher returns than US Government bonds, as they carry low credit risk due to their issuance by government-sponsored agencies; however, they are subject to unique prepayment risk, whereby declining interest rates may prompt homeowners to repay their mortgages early, reducing investor returns. US Corporate bonds yield higher returns but are associated with the highest credit risk among asset classes, influenced by the financial health of issuing corporations. Lastly, US Emerging Market bonds provide the highest returns but also exhibit elevated risk levels, driven by credit risk factors linked to the economic conditions, political stability, exchange rate policies, and interest rate environments of the emerging markets where these bonds are issued.

Results

The highest return is delivered by the Emerging Market Bonds Index, with an annualized return of 3.11%, while the lowest return is recorded by the US Government Bonds Index at 1.37% annualized. In terms of risk, the highest standard deviation of returns is observed in the US Corporate Bonds Index (5.84% annualized), whereas the lowest risk is associated with the US MBS Bonds Index (4.32% annualized). The Emerging Market Bonds Index also demonstrates the highest Sharpe ratio (0.681), while the US Government Bonds Index exhibits the lowest Sharpe ratio (0.285).

The risk parity model applied to data spanning from 2014 to 2023 gives an annualized return of 2.43%, an annualized standard deviation of 4.26%, and a Sharpe ratio of 0.569. The resulting portfolio consists of 19.49% allocated to the US Government bonds index, 17.30% to the US Supranational bonds index, 22.24% to the US Mortgage-Backed Securities (MBS) bonds index, 14.65% to the US Corporate bonds index, and 26.32% to the Emerging Market (EM) bonds index. Notably, the largest allocation is assigned to EM bonds, as this asset class offers the highest return with relatively low risk, as reflected in its lower standard deviation and higher Sharpe ratio.

Ideally, in a risk parity framework, the risk contributions should be evenly distributed across assets, ensuring no single asset disproportionately influences total portfolio risk. Government Bonds represent a significant portion of the portfolio weight but contribute proportionally to risk, reflecting their traditionally lower volatility. Supranational Bonds and MBS Bonds also maintain balanced allocations and moderate risk contributions, aligning with their role as stabilizing assets in fixed income portfolios. Corporate Bonds exhibit a relatively higher risk contribution compared to their weight, consistent with the higher credit and liquidity risks inherent in this asset class. EM Bonds contribute notably to the portfolio's overall risk despite a moderate weight, driven by their higher yield volatility and exposure to emerging market risks.

The portfolios of the Mean-Variance Optimization model

The optimization process is conducted by targeting the maximization of the Sharpe ratio using the MVO model. The optimization considers the expected returns of the assets in the portfolio in Table 4 below:

Table 4. Expected Daily Return

Assets	Expected Return
Govt Bonds	0.0055%
Supranational Bonds	0.0077%
MBS Bonds	0.0059%
Corporate Bonds	0.0122%
EM Bonds	0.0123%

Source: Authors elaboration using Excel solver

Under a scenario with short selling restrictions, portfolio optimization is carried out using the MVO model with a Maximum Sharpe Ratio strategy. The resulting portfolio construction yields the composition of weights, expected return, risk, and Sharpe ratio as presented in Table 5 below:

Table 5. Optimal portfolio of MVO model

Assets	Weight
Govt Bonds	0.00%
Supranational Bonds	5.25%
MBS Bonds	0.00%
Corporate Bonds	24.49%
EM Bonds	70.26%
Sum of Weight	100%
Avg. Daily Return	0.0121%
Annualized Return	3.04%
Annualized Std Dev	4.93%
Expected Sharpe Ratio	0.617

Source: Authors elaboration using Excel solver

The MVO model applied to data from 2014 to 2023 gives an annualized return of 3.04%, an annualized standard deviation of 4.93%, and a Sharpe ratio of 0.617. The optimized portfolio under this strategy consists of 5.25% allocation to the US Supranational Bonds Index, 24.49% to the US Corporate Bonds Index, and 70.26% to the Emerging Market Bonds Index, while the US Government Bonds Index and US MBS Bonds Index receive no allocation (0%). Consistent with the results observed in the Risk Parity approach, the MVO model also results in the largest allocation to Emerging Market Bonds, reflecting their relatively high return and comparatively low risk, as indicated by their standard deviation.

Comparation Result between Risk Parity and MVO model

Based on the portfolio optimization calculations using the Risk Parity and MVO methods, a comparison of the weight compositions and risk-return profiles between the two approaches is summarized in Table 6 below:

Table 6. Comparation portfolio between Risk Parity and MVO model

Assets	Risk Parity	MVO
Weight		
Govt Bonds	19.49%	0.00%
Supranational Bonds	17.30%	5.25%
MBS Bonds	22.24%	0.00%
Corporate Bonds	14.65%	24.49%
EM Bonds	26.32%	70.26%
Risk Return		
Annualized Return	2.43%	3.04%
Annualized Std Dev	4.26%	4.93%
Sharpe Ratio	0.569	0.617

Source: Authors elaboration using Excel solver

Table 6 shows that the MVO method delivers a slightly higher overall Sharpe ratio (0.617) compared to the Risk Parity method (0.569) over the entire observation period. Under the Risk Parity strategy, asset weights are more evenly distributed across asset classes, reflecting the method's emphasis on balancing risk contributions rather than maximizing expected returns. Conversely, the MVO strategy allocates disproportionately higher weights to higher-returning but riskier assets, notably EM Bonds and Corporate Bonds. This reflects MVO's sensitivity to expected returns, often resulting in concentrated exposures to maximize portfolio return potential.

Regarding Risk-Return outcomes, the Risk Parity portfolio exhibits a slightly lower Annualized Return compared to MVO, consistent with its defensive and diversification-focused design. The Annualized Standard Deviation for the Risk Parity portfolio is notably lower, indicating reduced overall portfolio volatility and better downside risk protection. The Sharpe Ratio, measuring risk-adjusted performance, shows that while MVO achieves a marginally higher ratio, the difference is relatively modest. This suggests that Risk Parity offers a more stable return per unit of risk, particularly appealing during periods of market turbulence.

Using the portfolio weight compositions derived from the Risk Parity and MVO methods, annual calculations of return, risk, and Sharpe ratio were conducted for each method over the period from 2014 to 2023. The results are showing in Figure 3-5 as follows:

Figure 3. Return (Annualized) Comparation of Risk Parity dan MVO model

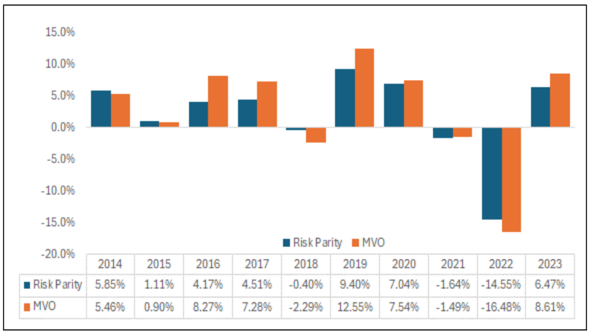


Figure 4. Risk (Annualized) Comparation of Risk Parity dan MVO model

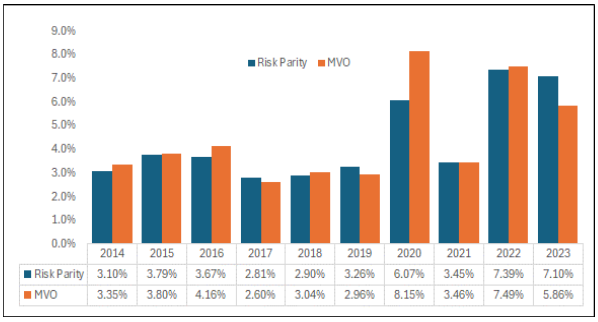
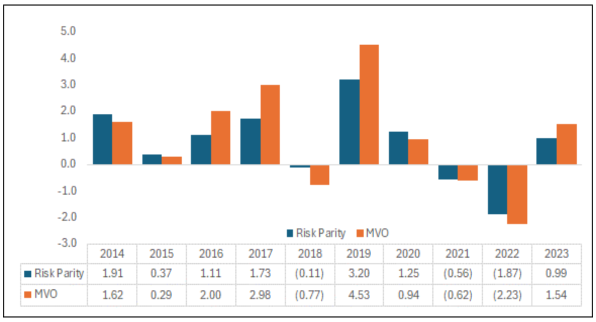


Figure 5. Sharpe Ratio Comparation of Risk Parity dan MVO model



Source: Authors elaboration

However, when examining the annual Sharpe ratio calculations on Figure 4, the Risk Parity method demonstrates greater consistency in achieving higher Sharpe ratios compared to the MVO method. As shown in Figure 5, the Risk Parity strategy outperforms MVO in six of the ten observed years (2014, 2015, 2018, 2020, 2021, and 2022), while the MVO method outperforms in four years. Notably, the years in which Risk Parity exhibits superior performance tend to coincide with periods of heightened market risk or crises (Costa & Kwon, 2020), such as the COVID-19 pandemic between 2020 and 2022. This suggests that the Risk Parity optimization method is generally more robust during periods of high volatility.

Referring to the return comparison in Figure 2, the MVO method tends to deliver higher annual returns in six of the observation years, whereas the Risk Parity method outperforms in four years. In contrast, the risk comparison in Table 3 reveals that Risk Parity achieves lower standard deviations in seven years, compared to MVO's advantage in three years. This indicates that the Risk Parity method exhibits superior risk management capabilities. Such characteristics align well with the preferences of institutional investors, such as central banks, who typically exhibit risk-averse behavior and emphasize strong risk management (Alhalaseh & Al Shawawreh, 2024).

In terms of allocation weights, the simulation results show that the MVO optimization method tends to concentrate allocations in specific asset classes, such as Emerging Market Bonds, US Corporate Bonds, and US Supranational Bonds. Conversely, the Risk Parity method distributes weights more evenly across all asset classes, avoiding excessive risk concentration in any single class. This characteristic represents an added value of the Risk Parity approach, as it enhances diversification benefits across multiple asset classes compared to the MVO method.

Backtesting between Risk Parity and MVO

Based on the results of Value at Risk (VaR) backtesting at 99%, 95%, and 90% confidence levels during the 2022–2023 period, the Risk Parity strategy demonstrated accurate and reliable risk estimation performance. The Kupiec Proportion of Failures (POF) test indicated no significant deviation from the expected violation rates under the Risk Parity optimization framework. With LR POF statistics falling well below the critical threshold, the Risk Parity strategy successfully passed statistical validation tests, suggesting that the VaR model employed is sufficiently robust to support investment decision-making and effective financial risk reporting. Moreover, Risk Parity consistently produced fewer exceptions compared to the Mean-Variance Optimization (MVO) approach, reflecting its more conservative stance in risk management—making it a suitable strategic preference for central bank reserve portfolio management.

Discussions

The empirical findings of this study reveal that the Risk Parity approach provides strong risk management advantages in USD-denominated bond portfolios compared to the traditional MVO model. Although the MVO model achieved a marginally higher overall Sharpe ratio (0.617 vs. 0.569), the Risk Parity approach demonstrated greater stability and resilience across different market conditions, particularly during periods of high volatility such as the COVID-19 pandemic and the post-pandemic financial tightening period. Notably, the Risk Parity portfolio maintained more balanced risk contributions and avoided excessive concentration in a few asset classes, unlike the MVO portfolio, which tended to allocate disproportionately toward high-return assets such as Emerging Market Bonds. This diversification feature of Risk Parity aligns with its theoretical objective and proved critical during stress periods, where risk concentration can lead to significant drawdowns.

Moreover, the year-by-year analysis highlighted that Risk Parity consistently delivered higher Sharpe ratios than MVO in six out of ten observed years, especially during crisis periods such as 2018 and 2020–2022. The back-testing exercise conducted during the high-volatility environment of early 2023, including the collapse of Silicon Valley Bank, further reinforced these findings: Risk Parity portfolios achieved superior risk-adjusted returns in four out of six months compared to MVO portfolios. This evidence supports the assertion that the Risk Parity strategy, by focusing on equalizing risk contributions rather than relying heavily on expected return forecasts, enhances portfolio robustness when markets are unstable and estimation errors in returns are amplified. Given these characteristics, Risk Parity presents an attractive alternative for conservative institutional investors, such as central banks, seeking consistent performance and strong downside protection across different economic cycles.

Additionally, this study underscores that the relative performance of portfolio optimization methods is highly context-dependent. While MVO may outperform in relatively stable or bullish environments by targeting return maximization, Risk Parity offers superior protection in turbulent conditions by mitigating systemic risks through better diversification. These findings contribute to the growing literature advocating for flexible, risk-based portfolio strategies, particularly for investors prioritizing stability, liquidity, and risk management over aggressive return-seeking behaviors. As global financial markets remain susceptible to shocks and regime shifts, the empirical evidence suggests that broader adoption of Risk Parity techniques could enhance long-term investment outcomes for risk-averse institutions.

CONCLUSION

The ten-year empirical analysis demonstrates that the Risk Parity approach provides a more stable and resilient framework for optimizing USD-denominated bond portfolios, especially for risk-averse institutional investors such as central banks. Unlike Mean-Variance Optimization (MVO), which achieved slightly higher Sharpe ratios through concentrated exposures to high-yield, high-risk instruments like Emerging Market and Corporate Bonds, Risk Parity maintained performance consistency by balancing risk contributions across asset classes. This balance allowed it to withstand heightened volatility during events such as the COVID-19 pandemic and post-crisis monetary tightening. By prioritizing risk diversification and downside protection over return maximization, the Risk Parity strategy achieved lower volatility, improved capital preservation, and more stable risk-adjusted returns. Future research should aim to enhance the model's real-world applicability by integrating dynamic rebalancing mechanisms, transaction cost considerations, and liquidity constraints, as well as expanding the Risk Parity framework to multi-asset portfolios. Incorporating regime-switching models or machine learning algorithms could further improve adaptive weighting and responsiveness to shifting macroeconomic conditions, strengthening the approach's utility across diverse investment environments.

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